DIMENSIONALITY ESTIMATION IN HYPERSPECTRAL IMAGERY USING MINIMUM DESCRIPTION LENGTH

Joshua B. Broadwater, Reuven Meth, Rama Chellappa
University of Maryland
Center for Automation Research
College Park, MD 20742

ABSTRACT

Numerous algorithms have been developed for hyperspectral automatic target recognition (ATR) applications. Many of these algorithms require estimation of a background subspace. The estimation of the background subspace has been addressed using multiple methods, but most of these methods assume a-priori knowledge of the background dimensionality. In order to automate the estimation of the background subspace, we present an algorithm based on minimum description length (MDL) that can identify the background dimension. Results show that the MDL criterion estimates the proper dimension of the background for ATR applications.

1. INTRODUCTION

ATR algorithms are a key component of the Army's Future Combat Systems. Of particular interest is the use of hyperspectral ATR algorithms for the detection of buried targets such as mines and underground facilities. Numerous algorithms have been developed for hyperspectral ATR and a number of these algorithms require the estimation of a target and background subspace. While the target subspace has been developed using modeling techniques independent of the image, the background is typically estimated directly from the image using algorithms such as N-FINDR (Winter, 1999), least squares techniques (Heinz and Chang, 2001), and singular value decomposition (Manolakis et al., 2001).

All of these techniques provide a background subspace but require the user to identify the dimensionality of the background subspace a-priori. This a-priori requirement prevents the adaptation of the techniques to full autonomous systems. In response to this, some algorithms have been proposed to automatically identify the dimensionality of hyperspectral images (Chang and Du, 2004); however, these algorithms have focused on spectral unmixing. Our approach focuses only on ATR applications where the dimension estimate is used to identify the size of the background subspace that leads to improved target detection and mitigation of false alarms.

2. DATA MODEL

The model used in this paper is the linear mixing model (Hapke, 1993). The linear mixing model assumes a pixel is made up of endmembers, each with its own abundance. Endmembers are the spectra representing the unique materials in a given image. For instance, in an image that contains dirt, grass, and road, the endmembers would be the corresponding unique spectral signatures for each of these materials. Abundances are the amount of each material within a given pixel. Mathematically, these concepts are expressed as

$$x = Ea + n, \quad a_i \geq 0 \,\forall i, \quad \sum_{i=1}^{M} a_i = 1 \tag{1}$$

where x is an $D \times 1$ vector that represents the spectral signature of the current pixel, M is the number of endmembers within the image, E is an $D \times M$ matrix where each column represents the i^{th} endmember, a is an $M \times 1$ vector where the i^{th} entry represents the abundance value a_i, and n is assumed zero-mean, iid Gaussian noise with variance σ^2. Therefore, given a way to estimate the endmembers and abundances, what M should be chosen such that the model above provides the best fit to the data with lowest dimension?

3. MINIMUM DESCRIPTION LENGTH

MDL was proposed by Rissanen (Rissanen, 1978) and independently by Schwartz as the Bayesian Information Criterion (Schwartz, 1978). MDL provides an estimate of the in-sample training error for model selection purposes. The estimate has been shown to be unbiased and consistent. The MDL can be written mathematically as

$$MDL = -2 \log L(x, \alpha) + d \log N \tag{2}$$

where $L(x,\alpha)$ is a likelihood equation based on the data x with parameters α, d is the dimension of the model, and N is the number of training samples used in the likelihood equation. In (1), the pixel can be modeled as a normal distribution with mean $\mathbf{Ea}$ and standard deviation $\mathbf{I}\sigma^2$.

Since the pixel is being modeled with this distribution, a likelihood equation can be derived such that

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14. ABSTRACT

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$$L(\mathbf{x},\hat{\mathbf{E}}\hat{\mathbf{a}},\mathbf{I}\hat{\sigma}^2) = \prod_{i=1}^{N} (2\pi\hat{\sigma}^2)^{-\frac{D}{2}} \exp(-(\mathbf{x}_i - \hat{\mathbf{E}}\hat{\mathbf{a}}_i)^T (\mathbf{x}_i - \hat{\mathbf{E}}\hat{\mathbf{a}}_i)/2\hat{\sigma}^2) \quad (3)$$

where D is the number of spectral bands in the hyperspectral image. Using this likelihood and simplifying, the MDL for the model in (1) can be calculated so that

$$MDL = \sum_{i=1}^{N} (\mathbf{x}_i - \hat{\mathbf{E}}\hat{\mathbf{a}}_i)^T (\mathbf{x}_i - \hat{\mathbf{E}}\hat{\mathbf{a}}_i)/\hat{\sigma}^2 + d\log N \quad (4)$$

Note that a number of parameters must be estimated to calculate the MDL. The variance is calculated directly from the original image. The endmembers and abundances are calculated for this work using the Unsupervised Fully Constrained Least Squares (UFCLS) algorithm (Heinz and Chang, 2001). Finally, the parameter *d* must be calculated which is a measure of the "dimension". In this application *d* becomes the number of endmembers multiplied by the number of spectral bands. Replacing *d* into (4) results in

$$MDL = \sum_{i=1}^{N} (\mathbf{x}_i - \hat{\mathbf{E}}\hat{\mathbf{a}}_i)^T (\mathbf{x}_i - \hat{\mathbf{E}}\hat{\mathbf{a}}_i)/\hat{\sigma}^2 + MD\log N \quad (5)$$

4. EXPERIMENTAL RESULTS

To test the ability of the BIC to estimate the "best" number of endmembers for ATR, MDL values were calculated for varying number of endmembers in both synthetic and real hyperspectral images. The MDL values were then compared using the performance of a hybrid target detector (Broadwater et al., 2004). At the number of endmembers where the MDL obtains a minimum value, the detector should provide its best performance.

The synthetic image was created using an AVIRIS image from the Moffett Field data set. Target signatures were inserted at known locations with varying abundances. The results in Table 1 show that the MDL and detector achieved their best performance with five endmembers.

Table 1: MDL Results for Synthetic Image

# Spectral Signatures	False Alarms	MDL
2	7586	21358
3	32	14550
4	128	3736
5	1	1259
6	3	1409
7	3	1615
8	2	1799
9	3	1998
10	3	2208

The second experiment was performed on a hyperspectral image of a live mine site. The image contained 1200×256 pixels with 256 spectral bands in the visible to short-wave infrared spectrum. Forty-eight surface mines were present in the image. Twenty-four mines were M19s and the other twenty-four were M15s.

The experiment was designed to identify only the M19 mines in the image. The MDL estimated that nine endmembers should be used. When using these nine endmembers, the detector was able to find all 24 M19 mines with zero false alarms. When the detector used less than nine endmembers, false alarm rates increased significantly.

5. SUMMARY

The MDL criterion has been demonstrated as a way to estimate the number of endmembers for ATR applications. In both synthetic and real hyperspectral images, MDL automatically chose the number of endmembers that provided the best overall detection results. Based on this work, the MDL criteria can be used to implement a fully automatic method to estimate the structured background for ATR applications.

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